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Textual factors in online product reviews: a foundation for a more influential approach to opinion mining

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Abstract While data mining is well established in practice, opinion mining is still in its infancy, with issues in particular around the development of methodologies which effectively extract accurate, reliable, influential and useful information from the raw opinion data collected from informal product reviews. Current approaches adopt a single-variable approach, focusing on individual metrics—word length, the presence of keywords, or the overall semantic orientation of terms within the data—while neglecting to evaluate whether these individual artifacts are indicative of the tone of a given review. This approach has significant limitations when we move from trying to merely evaluate whether an online opinion is positive or negative, to trying to evaluate how likely it is that the opinion will influence others. Given this issue, one promising avenue would be to evaluate the general analysis approaches utilized by opinion mining algorithms and identified in the literature in terms of how accurately they reflect how people actually interpret and are influenced by electronic online reviews. Through interviewing and a follow up survey of 136 participants, the validity of the approach in terms of ascertaining the tone of a piece of text can be evaluated, as well as the identification of measurable factors within text which make a given opinionated text more or less influential in an online context, further facilitating the development of more effective multivariate opinion mining approaches. Furthermore, the identification of factors which make an online opinion text more or less persuasive

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helps to facilitate the development of opinion mining approaches which can evaluate how likely a review is to affect an individual's decision making.

Keywords Electronic word of mouth communication (eWOM) · Online product review · Opinion mining · Consumer decision making

1 Introduction

Due to the improved ease of communication, the product review, whether in a forum context or on a website such as epinions.com, has emerged as a significant source of information for potential consumers of goods and services [9]. The importance of word of mouth communication has long being recognized in the academic literature as a significant determinant of consumption [30], with word of mouth communication only increasing in importance with the emergence of Internet-based mechanisms. There is a plethora of online communities existing around product niches, with examples in the literature ranging from relatively mainstream goods such as books [5], through to more esoteric goods such as craft beers [6], with all instances showing online word of mouth exhibits a significant impact on consumption behavior.

However, what remains to be established is a coherent model explaining which factors of an online product review shift consumer perception of a product, and how these relate to consumer decision making around a given product. While a range of beliefs are held about which particular aspects of reviews are important for discerning opinion, the lack of a validated model makes it impossible to empirically establish whether the current approaches being used to discern the influencing characteristics of a product review are correct, or identify ways in which they could be improved. Therefore, this paper has sought to develop this validated model, so that progress in this area can move forwards on a more reliable footing. The development of an understanding around what aspects of online product reviews influence consumer decision making is becoming increasingly important, given the benefits for organizations in developing improved marketing and product design approaches through the utilization of word of mouth information.

Based on the conceptual model initially developed—drawing from the material in the existing literature around this area of investigation—this research contributes to academic areas in several ways. In particular, the factors currently discussed in the literature—word length, positive/negative key features, overall positive/negative nature, keywords and quantitative information—were found to be aspects of other factors, and did not have direct linkages and strong influence themselves. This suggests that these established factors utilized by opinion mining—while suitable for conveying positive/negative orientation—are insufficient for moving beyond this towards identifying how the opinion presented affects/influences readers. Other factors such as information accuracy, persuasive words and customer support were highly influential and need to be included in opinion mining.

For this reason, this paper is not wholly dedicated to the improvement of opinion mining approaches, but rather represents an extension of opinion mining—an idea we will call *influence mining*. Influence mining comprises an extension of the purpose of

opinion mining, moving beyond the classification of semantic information (as opinion mining is defined by Esuli and Sebastiani [14]) and its manipulation and use by data mining systems. This is still a relevant aspect for influence mining, and the techniques developed and utilized for semantic classification remain essential, but it also entails the development of a disciplinary understanding of the role that the individual psychology of the reader plays in the materials' interpretation, and how the linguistic characteristics of a written text influence human perception. As exhibited by the range of materials utilized in this research, it is heavily cross disciplinary—again, similar to opinion mining—but the presence of the *reader* as a relevant factor presents a broad range of new academic frontiers. Research has been done which seeks to look beyond the text presented online, seeking to extract information about the author's intended actions based on the online text presented [21]—albeit with a substantially different purpose from that envisioned for use in influence mining. However, this is representative of an emerging trend in both research and practice—the move from analyzing what a text *says* (its literal meaning), to what it *means—evaluating* what the author's intended meaning is when writing a text, what the reader's perception of a text is when reading it, and how we can extract and utilize this knowledge in systems to deliver economic or social advantages.

Perhaps one avenue for further investigation in this area would be to analyze the approaches already being utilized by entrepreneurial firms leading development in this area. Firms like Visible Technologies (http://www.visibletechnologies.com/) and Radian6 (http://www.radian6.com/) are leading the field in this area, developing approaches for monitoring the informal communications between consumers, and leveraging this capability to provide knowledge to their clients (including Fortune 500 firms such as Microsoft and Xerox) around consumer perceptions of their brand and product portfolio. While their approaches are proprietary, a cursory analysis of material on their websites indicates that they are utilizing some metrics which are similar to those identified in the model developed in this paper, such as discussion of non-product aspects—presented by Radian6 as "on-topic posts" [37]. This suggests that further investigation of the factors being utilized by industry, through field research or similar, could yield valuable insights into how the factors identified in this paper can be measured or refined. The implications of this research for practice are discussed.

This research contributes towards the development of approaches around the extraction and analysis of influence. While the focus of data collection and analysis is on online textual reviews of a single product, the findings suggest that it is now possible and reasonable to start analyzing the interpretation of informal communications, and the influence this has on decision making through the developments within the field of opinion mining. Given the benefits that can be derived from the vast quantity of informal communication now occurring, due to the emergence of Web 2.0 and the preponderance of informal communications which have resulted from this [38], these communications now represent a valuable font of information for the development of improved product development, marketing and other efforts which benefit from a better understanding of consumer perception and use of a firm's products. As proven by the emergence of start-ups in this area, it is now technologically feasible to analyze the influential nature of online text. Given that the factors identified are measurable

and exist within a coherent model, it is reasonable to see future developments in the area derived from this research.

Furthermore, the abstraction of factors into discrete units offers other benefits to practice. In particular, it suggests that a similar approach could be utilized to identify non-product related text where both orientation and influence are significant—such as the identification of individuals who are writing texts which are both politically extreme in nature, and likely to influence others towards these views. Thus, systems could be developed and utilized by government agencies to monitor the correspondence of these individuals, in order to mitigate harm to society. This is but one example of the extensibility of the approach used. Due to the broad categorization of "features" as the relevant metric, features need not correspond to physical aspects of a product: they could serve as the distinguishing traits of an idea or philosophy as well. It is thus evident that the implications of this research, in making a solid contribution towards the extraction and evaluation of the influence of online text, mean that the models, constructs and factors presented are likely to be of benefit for the development of data mining approaches and methodologies which seek to analyze and derive benefit from online informal text.

This paper is developed in several stages. First, the decision making process is outlined and evaluated for the potential manner in which informal product reviews affect the process individuals utilize in reaching their purchasing decisions. Subsequently, the nature of these reviews as word of mouth communications is evaluated, identifying how it differs from other types of communication, and the unique nature of reviews as communications. The current utilization of these reviews in opinion mining is then analyzed, in particular the narrowed focus of the current literature on single-factor solutions. From this, a conceptual model is developed and expanded to serve as the basis of enquiry. A methodology to address the research question is developed, followed by the results derived from its application. Finally, the findings of this research, and its contribution and implications for academics and practitioners are presented.

2 Related work

2.1 Potentially influential factors

The utilization of online product review information for organizational purposes is an emerging area of interest. However, some caveats exist. While some attention has been paid to the development of competitive intelligence through data mining approaches in areas such as research and development [35], the possible applications of opinion mining approaches appear to be limited in the academic literature. Furthermore, a number of factors have been identified as measuring opinion, but no unified approach has been taken to establish these factors as truly representing the factors which consumers use to develop their opinion based on word of mouth communication.

Hu and Liu [24] seek to demonstrate a general way in which opinion mining can be utilized on product reviews, using standard opinion mining approaches, but also proceeding to summarize the products analyzed on a variety of features, aggregated by

their semantic orientation—they use the demonstration of a camera's picture quality. This approach provides more granularity than merely assigning a positive/negative orientation to each individual review, allowing a more specific "drill-down" into the good and bad features of a given product. This has several advantages over assigning an overall positive/negative value to an individual review, through allowing organizations to perceive what aspects of their products consumers consider positive—and thus serve as the basis for marketing—as well as which features are considered deficient or negative, and thus in need of product design attention.

The findings of Chevalier and Mayzlin [5], as well as Chatterjee [4], related to the overall nature of the review, are also worthy of consideration. Chevalier and Mayzlin showed through their research on two online book sellers that an incremental negative review has a greater impact on sales than an incremental positive review. Furthermore, they established that users do read review content, even if an average rating for a product is available (ibid.), thus emphasizing the importance for organizations of analyzing the word of mouth content itself, rather than simple metrics such as ratings. Chatterjee [4] also identified that negative product reviews have a more significant impact than positive reviews, but furthermore that the reader's predisposition towards receiving and processing word of mouth communications is significant in determining the impact of word of mouth communication. While this is undoubtedly true, the reader's individual nature cannot be analyzed effectively in a data mining application, due to the inability to assess individual readers' predilections towards a review automatically. However, the readers' predispositions can be aggregated and held as a profile, which, although likely to vary between consumer groups, is implementable in a data mining application. Furthermore, due to the nature of software, this aggregate consumer profile is capable of being calibrated to suit the consumer segment being studied. Thus, while the nature of an individual will shape the manner in which a review influences their perception, an aggregation of individuals is likely to provide a more consistent basis through which applications can be developed to exploit the benefits of online word of mouth previously identified. A summary of review features that have been used in previous research is shown in Table 1. These selected features do not necessarily represent influential features.

2.2 The decision making process

Of importance towards understanding the relevance of online product reviews in influencing decision making is developing an understanding of how consumers go about decision making, and the manner in which it is influenced. There are traditionally five steps taken in the consumer decision making process (Fig. 1) [12]. Of these five steps, the one of particular interest for the impact of product reviews is Search. Search is comprised of the consumer, upon identifying a problem, evaluating the alternatives available to them for action, through the collection of relevant information and experiences based on available stimuli (ibid.). This model is of particular interest because it can be seen that consumers are increasingly turning to the Internet in order to acquire potential information about a product [34]. Furthermore, Internet-based user-generated product information has been shown to be more effective in attracting consumer interest about a product than marketer- or corporate-generated content [2].

Table 1 Review features used in previous research

Authors	Review features selected	Context/data	Techniques/methods
Zhang et al., (2011) [45]	Review content; Relevance of a review to product; quality; Helpful vote; Total votes; Posting date; Durability of reviews	SLR camera and TV; Amazon.com	Ranking based on importance of review
Yu et al., (2011) [43]	Important aspects (features of a product); Pro and cons reviews	Cnet.com, Viewpoints.com, Reevoo.com, Gsmarena.com; Camera, Laptop, MP3, Phone	Aspect ranking based on frequency
Huang et al., (2011) [27]	Information quality; Authenticity; Authority; Interestingness	210 Students from two China universities	Survey
Gerdes et al., (2010) [19]	Positive words/Negative words	Hotel; CheapTickets.com	Difference between proportion method (DBPM)
Zhang & Narayanan (2010) [46]	Product features; Price; reliability	Digital camera and Television; Amazon.com	Ranking
Hu, Gong & Guo (2010) [26]	Product features	Digital camera, DVD player, MP3, mobile phone	Frequency
Zhang & Tran (2010) [47]	Opinion words; Product features; Product parts	Digital cameras; Amazon.com	Linear Ranking
Zhang, Cracium & Shin (2010) [44]	Positive review; Negative review; Persuasiveness of review; Helpful Rating; Star rating; Price; Product features; Web page length; Typed characters; Review lifetime; Total reviews	Software purchase; Amazon.com	Experimental design
Hu, Liu and Zhang (2008) [25]	Favorable news; Unfavorable news; Reviewer's reputation; Reviewer exposure; Product coverage; Age of product	Amazon.com; Books, DVD, videos	Quantitative
Hu & Liu (2004) [24]	Product features, opinion words orientation	Digital camera, DVD player, MP3, mobile phone; Amazon.com, C|net.com	Features based summarization; Association rule mining

Fig. 1 Engel, Blackwell and Kollat five stage consumer behavior model (1978)

The Internet provides an easy and convenient mechanism through which consumers can access a vast range of information on a given product, and thus its impact on decision making is likely to continue to grow in prominence [33, 34].

Based on this understanding of the consumer decision making process and the emerging importance of the Internet in regard to the search for information, the influence that online product reviews in particular exert on consumers should be considered. First, however, it is important to understand how reviews are related to the other sources of communication available on the Internet.

2.3 Word of mouth communication

A broad range of information is available on the Internet about potential products, ranging from traditional marketing material [39], the use of new corporate marketing tools, such as corporate web pages which are tailored to provide influential material to consumers as well as investors [15], through to the use of word of mouth communications—interpersonal communications where none of the participants are marketing sources [3]. Word of mouth communications, in contrast to the other sources of information available online, are generated by the actual consumers of a given product or service, and thus are seen as more credible than materials provided via traditional marketing techniques [2]. Furthermore, the level of word of mouth communication is continuing to increase, with Internet trends such as Web 2.0 resulting in a massive increase in the amount of user-generated content available, resulting in word of mouth communication becoming a more significant influence on consumers' purchase decision making [38].

Word of mouth communications are found on the Internet in several different environments. These range from social communities built around a shared interest [11] and product reviews and evaluations on distributors and retail sites, such as comments on amazon.com [5], through to comments on independent forums specifically designed for consumers to express their opinions on a broad range of products, such as epinions.com [9]. While word of mouth communication exists in a multitude of settings online, the common factor is that it is built around the consumers' subjective opinion of a product, rather than objective facts or specifications of the product itself. Furthermore, these word of mouth communications can be divided into two categories—the supply of information, and the discussing of information. The supply of information occurs when a user in a given setting contributes their experiences with a given entity, whether that is a product, service or method, while the discussion of information emerges when other users discuss the findings of the initial supplier and generate new ideas and opinions [11]. For the purposes of this research, we will focus on the supply of word of mouth information rather than the organic emergence of ideas through discussion, and thus focus on information supplied in the form of a product review.

From this basis, we can now move to analyze the manner and degree to which reviews, as word of mouth communications, exert influence upon consumer decision making, and the resultant consumption of goods and services.

2.4 Influence of reviews

A significant body of material exists around the influence exerted by reviews. Gemser, Van Oostrum and Leenders [18] identified x two perspectives in the literature on the

effect of expert reviews—the Influence perspective, where the review influences the consumers' decision making; and the Prediction perspective, where the review serves as a predictor of future consumer consumption but does not influence consumer decision making about the product. They found that reviews exert an influencing effect on consumer consumption, but the degree of influence they exert on the consumers' consumption is dependent on the type of product, with niche products (art-house movies) exhibiting a statistically significant difference in consumption based on reviews that is not shown in mass-consumption products (mainstream). This finding, while of limited relevance to the area of online product reviews due to the inherent difference between expert reviews in traditional media and user-provided reviews in an online context, is of interest due to its suggestion that products targeted at a more specific audience are more likely to experience differences in consumption based on review content. Concerns around the applicability of research based upon expert reviews for examining online product reviews are alleviated however by the findings of Dellarocas, Awad and Zhang [10], who found that online consumer reviews are representative of the general consumer base. Dellarocas et al. also found that online consumer reviews are highly accurate predictors of movie success, explaining between 68 and 88 percent of the variance of movie box office success, far exceeding the predictive value of professional critics.

The influence of reviews becomes of particular interest with the emergence of business models built around a Long Tail approach—where businesses leverage e-commerce to sell products which, while not the top selling products (or "hits"), have an audience that can be catered to profitably [1]. Anderson [1] outlines how the Internet, through shifting product consumption from being heavily determined by geographic factors related to how many people live near each retail outlet to consume the product to a situation where geographic concerns are irrelevant for distribution, is enabling the success of products which would have been uneconomic to provide previously. He demonstrates this through showing how products which are of interest to a potential audience can become successful, through their word of mouth resulting in a loop which leads to greater consumption. High-quality but little-known products thus benefit from positive consumer sentiment, resulting in increased consumption by consumers who then review the product themselves, often positively. If we take this concept in conjunction with the findings of Gemser, Van Oostrum and Leenders [18], we can see that word of mouth communications are likely to be able to exert a significant influence in a long tail economic approach, with reviews exerting an overwhelming influence on products which are not noteworthy enough individually to have had extensive marketing campaigns or other communications that influence consumption. Thus, we can derive that the information contained in reviews is likely to be of significance in both shaping consumer decision making around a given product, as well as of importance for organizations seeking to monitor the success of their product.

Chatterjee [4] also addresses the influence of product reviews on consumer decision making. He identifies that online word of mouth sources are implicitly "weak ties"—that is, they are provided by total strangers, as opposed to the "strong ties" which can exist in traditional communications, where consumers know the individual who is communicating the word of mouth information—and thus utilize their knowledge of the individual in deciding how much validity to ascribe to the information

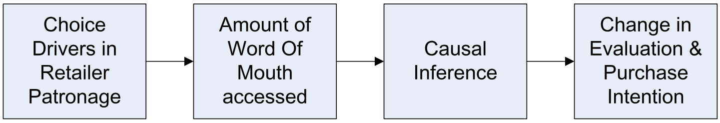

Fig. 2 Online word of mouth influence effect [4]

conveyed. Chatterjee uses this realization to establish a model depicting how word of mouth communications in online settings influence purchasing decision making (Fig. 2).

Having established the manner in which reviews exert influence upon consumers, and having established that online word of mouth communications are an important source of consumer information, we can now move towards analyzing potential applications they could be utilized for by organizations.

2.5 Online product reviews—applications

Product reviews in an online context hold particular promise for a variety of applications. While there is a large number of product reviews to be found on the Internet, contributions to online communities are only made by a minority of interested parties [11]. Furthermore the ability for contributions to be made at effectively no cost, the reach of such communications to a large audience, and the perception of credibility held around word of mouth communications means that they are a useful source of information for analysis. Kozinets [29] developed the idea of netnographic research, which leverages the accessibility of online communities and the ability to observe without being a part of the environment to facilitate new qualitative research approaches, particularly related to the development and conducting of more effective marketing research.

Word of mouth communications have also been identified as an important source of information for areas outside of marketing. Godes and Mayzlin [20] identified the potential importance of word of mouth communication in determining product success. They found that the fundamental limitation of organizational management of word of mouth at present is the difficulties which exist around its measurement, a critical issue which must be resolved given their observance that the existence of a publicly accessible reservoir of person-to-person communications is unprecedented in history (ibid.) Thus, approaches which could be utilized for measuring word of mouth communications become important. While Godes and Mayzlin outline two traditional approaches which have been utilized in order to collect similar information—inference and surveys—a third approach which has recently emerged is the use of data mining to extract opinions automatically.

2.5.1 Data mining

Data mining is the process of discovering hidden information from data [22]. It entails utilizing a combination of database technologies, statistical approaches and information processing techniques in order to extract non-obvious information which

exists as patterns within a collection of data. Data mining comprises two distinct but inter-related processes: knowledge discovery, where explicit information is extracted from the data; and predictive modeling, where information is manipulated and used in order to generate predictions related to an area of interest [16].

Data mining has a variety of applications in a business setting. Through gaining better awareness of the internal and external business environment, businesses can pursue strategies which achieve superior levels of competitive advantage [40]. Business intelligence, a broader concept which focuses on the application of data mining to a business setting, has furthermore been shown as the way that market-leading firms are implementing and achieving competitive advantage, through the superior awareness data mining grants to the development of business strategies and improvement of internal and external processes [8]. Research on the use of data mining approaches to facilitate the achievement of organizational value from product reviews is well-known. Hu et al. [26] used both explicit and implicit product features mined from online reviews. Zhang and Narayana [46] used a product feature-based ranking technique to mine online customer reviews. Hu and Liu [24] used data mining and natural language techniques for product features extraction and summarizing. All these approaches could provide organizations with competitive strength and insights about their products and competitors' products in the market. However it is not yet certain whether these features are indeed influential or merely presumed so by the researchers. In this study, the influential factors identified can provide the foundation for certainty, with features' weights and context integrated into a more influential review summary for organizations or consumer recommendation systems. For example the length of the review could be an influential factor but was not deemed important in all the above features extraction techniques. The information contained in a review is unstructured textual information, and the entity of critical importance within it is the nature of the opinion it contains. Due to the difficulties of dealing with subjective and unstructured information with traditional approaches, the field of opinion mining has emerged as critical for the development of data mining related approaches in this field.

2.5.2 Opinion mining

Opinion mining is a recently emerged field which specializes in discerning the opinions expressed on a topic [14]. It is a cross-disciplinary field, drawing upon research into information retrieval and computational linguistics in order to identify aspects of a piece of text which are important in the semantic classification of text. These aspects are stated as identifying whether a term used within a review is being utilized in a subjective [expressing an opinion] or objective [not expressing an opinion] manner [13], the semantic orientation [whether the word utilized is positive or negative] of the text [7, 42], as well as identifying the degree of strength of the semantic orientation—whether it is strongly positive or negative, or whether it is only slightly so [13, 17]. Through utilizing this information, approaches can be used to identify the overall theme of an opinion in text with a high degree of accuracy [17].

The utilization of opinion mining provides the necessary metric of opinion which is needed for transforming online word of mouth opinions into information which

can be automatically processed and analyzed, and facilitates the utilization of data mining methods to extract information, removing the burden of manual identification and analysis. Thus, with a process to extract useful information from online product reviews, methods through which this information can be applied in an organizational setting can be identified along with approaches. However, before these methods can be utilized, an understanding of the factors within reviews which are important to measure to determine consumer influence needs to be established.

Based on the literature in the problem area, a gap exists in the knowledge base, with limited established research as to what particular factors contained within an online product review influence consumer decision making. The existing body of literature appears to hold an a priori belief that there are one or two key factors contained in word of mouth communications that shape consumer decision making. Thus, it would be of interest to empirically establish the set of textual factors contained within online product reviews which influence consumers' decision making. Through identifying these factors, organizations will be able to develop more effective technological approaches to collect, analyze and utilize word of mouth communication in their product design and marketing endeavors.

3 Research question

As outlined above, the research question is:

RQ *What are the relevant factors in a product review and to what extent do they influence the readers' decision making regarding the product?*

Following from, and related to establishing whether product reviews do exhibit the level of influence often ascribed to them, is establishing the mechanism through which they influence decision making. Due to the textual nature of product reviews, certain interpersonal dynamics which influence physical communication settings are irrelevant, however identifying what particular aspects of review text are influential is of interest for developing approaches which seek to extract and utilize this information.

Before progressing to identifying candidate factors, however, the link between consumers' perception of a review and decision making must be established. For the consumer decision making process and its identification of information search as part of the decision making process [12], we can establish that information gathered by consumers influences their decision making. Therefore, we can logically induce that information must be perceived to be gathered, and that the perception of this information will determine the influence it has on decision making. Therefore, we can take the consumer's perception as a prerequisite to decision making, and thus analyze the impact of each factor on the consumer's perception, holding it a priori that perception influences decision making.

Several factors have been identified in the literature. Gerdes, Stringam and Brookshire's [19] approach to developing an opinion mining system is also of interest. Their two-factor approach utilizes a set of *keywords* and *word frequency*. Keywords are a

group of meaningful words describing a particular concept in the review. Word frequency is the number of times a particular word appears in the review. They found several interesting characteristics of product review information. In particular, they identified that *negative reviews* are more distinctive than *positive reviews*, as well as that positive reviews are three times more common than negative reviews. This may explain some of the findings of Chevalier and Mayzlin [5] and Chatterjee [4]. The utilization of keywords to discern opinion, as covered above, is an established opinion mining approach for determining whether a review is positive or negative, but how influential the presence or absence of a particular keyword is on the readers' decision making itself has not been established. Furthermore, they found that word count could be effectively utilized in improving the accuracy of classification of reviews as positive or negative. Gemser et al. [18] also identified in particular, the overall number of reviews and the size (dimension) of the film reviews to be important variables that influence the early box office revenue of movies. They found that the "visibility" of a review—how prominent it is among available information—influences its effectiveness. Hence the placement of review content such as feature comparison tables and pictures is likely to be relevant in an online setting. Finally, Hsee et al. [23] analyzed the manner in which *quantitative information* influences consumer decision making. Quantitative information refers to specifications or numbers that describe product attributes, such as the weight of a mobile phone, battery life, and camera resolution and so on. They found that quantitative information has a significant impact on shaping consumers' decision making, regardless of other details and ideas known about the product. It would be interesting to see whether the presence or absence of quantitative information in a review is a significant factor in influencing consumer decision making.

Based on the above, we have established a few potential candidates as factors which may influence consumer decision making. Furthermore, in order to extract more utilizable information from word of mouth communications for organizations, it is of interest to identify whether particular aspects of a product, when analyzed, are of concern: whether the performance of one particular aspect of a product is generally seen as shaping the overall positive/negative impact on the readers' decision making, or whether the readers' decision-making process is more holistic. Finally, there may be new unidentified factors that, while not yet appearing in the literature, are significant in influencing consumer decision-making based on their reading of a review. These additions thus result in Fig. 3.

Thus, the development of an appropriate research design, which analyzes consumers to see what individual weight they assign to these factors, should be able to effectively answer the posited research question, with the resulting benefits which derive from this, as outlined above.

4 Methodology

4.1 Research methods

While this study is predominantly a mixture of qualitative and quantitative research, aspects of quantitative research were utilized to help triangulate and verify the find-

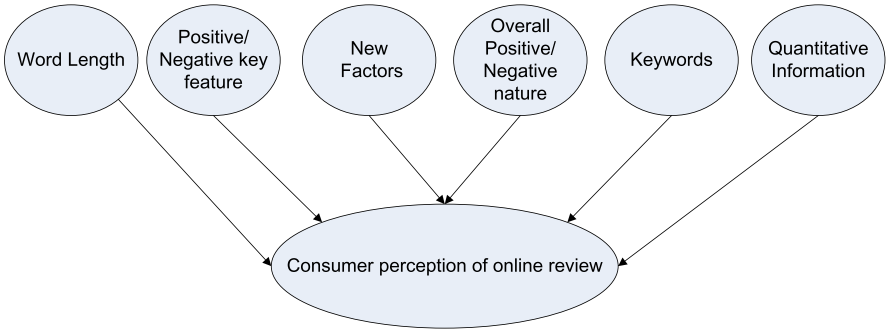

Fig. 3 Candidate factors that influence consumer decision making based on their perception of a review

ings derived from the initial data collection method: interviews with volunteer participants. Quantitative research is primarily focused on the collection and analysis of numeric data, while qualitative research is primarily concerned with the collection and analysis of non-numerical data [36]. While this difference appears simple, quantitative and qualitative research also each have a different method of thinking and world-view, with Kaplan and Duchon [28] noting that pure quantitative research is inadequate in social science field research—there are simply too many variables to control, and that thus some qualitative research is required in order to develop a deeper understanding of the situation. Based on the ideas of Kaplan and Duchon, as well as the positivist approach that this research is coming from, this research utilizes predominantly qualitative methods, in order that the qualitative findings from the reviews can be verified somewhat, as well as providing stronger evidence around the validity of the factors identified in the candidate model (Fig. 3).

4.2 Data collection approach

In the first phase of the research we employed elements of both structured interviews and unstructured interviews as the method of data collection. A structured interview uses a set of predefined questions that are asked in the same order for all respondents. In an unstructured interview neither the question nor the answer categories are predetermined. Instead, they rely on social interaction between the researcher and the informant [31]. For this study a structured interview approach was predominantly used in the evaluation of existing candidate factors, while a more open approach was considered appropriate for investigating and extracting insights from the research participants around new factors which may exist, as well as aspects of the established candidate factors which may require greater delving into than a structured approach would allow. It was also identified that six participants [32] should be interviewed initially to provide sufficient material to allow analysis into the factors involved, as well as providing a reasonable number of reviews to be covered, so that the findings would be sufficiently meaningful. Interviewees were selected without controlling for gender, age or ethnicity, with the major criterion being that they had utilized a cellular phone before (given the amount of information discussed in the reviews which was related to cellular phones). Research participants were presented with three reviews

of the product, distributed according to the criteria identified in examples of online product reviews. All interviews were audio recorded to allow for transcription.

The second phase of the study used a survey with questions derived from the results of the interviews focusing on textual factors of online reviews. The survey collected the Likert scale information needed for triangulation and verification of factors and provided weights for the opinion mining algorithm.

4.3 Data analysis approach

The qualitative data analysis approach utilized in this research was interpretive, with the researchers integrating the factors identified during the data collection into a coherent model. This entailed two steps:

Coding of non-candidate factors: Interview responses were coded through an open coding approach [41]. This was iterated, with the factors identified in the results section (under *Interview—Results*) being the result of this coding. The coding of this material was supported by the use of the NVivo 8 software package, allowing for the rapid testing of hypothesized relationships and comparison between individual codes, with these codes being merged into a higher level factor where appropriate.

Evaluation of factor ratings: The Likert scale responses were derived from the survey, with descriptive statistics generated to allow the interpretation of their findings in relation to the factors identified through coding, as well as the verification or dispelling of the candidate factors identified in the initial conceptual model (Fig. 3).

5 Results

Applying the methodology outlined above gave the following results. Each major source of data—the interviews conducted with the participants and the survey results—is presented. Factors identified from the coding of the interviews are presented, as well as the descriptive statistics used, and any interesting patterns or relationships identified within the data.

5.1 Interviews—results

The results of the interviews have been coded into 11 factors, drawn from a total of 280 individual coded items. A list of these codes is presented in the table below (Table 2), ordered by the percentage of text they occurred in.

Based on these top level codes, they were developed into factors for use in the evaluation of the conceptual model. Thus, the researchers grouped this material into distinct factors, based on what they identify. These are aligned by the common topic referred to in each item. We can thus proceed to outline the factors identified within these interviews.

5.1.1 Factors associated with positive/negative alignment

The following are factors which—based on participant responses and the interpretation of them by the researchers—are related to the positive/negative alignment commonly analyzed in opinion mining.

Table 2 Occurrence of individual codes in transcribed interviews

Code	Occurrence (discrete count)	No. of participants who mentioned factor
Depth of description of features	69	6
Formality of language	31	4
Balance of positive/negative features	30	6
Perceived objectivity of review	29	5
Relevance of features to reader	29	5
Range of features covered	21	6
Discussion of non-product aspects	20	5
Semantic orientation of words	19	4
Explicit statements	16	6
Presence of very negative features	12	4
Comparisons to other products	4	2
Total	*280*	*6*

5.1.2 Balance of positive/negative features

This factor refers to the overall balance of how many positive aspects of the product reviewed are discussed, compared to how many negative aspects are discussed. The term "feature" is used in this and the following factor, as this is what the participants in this research associated with positive/negative—describing features. It appears that respondents are internally calculating how positive or negative a review is by counting how many positive features there are compared to negative features, and using this as a guide to ascertain whether the review was positive overall or negative—even if the review explicitly states it is positive or negative. One participant identified it as:

> "*I'd say mostly positive. Other than the fact that it didn't cut the mustard for that person in particular, because of the Internet and the yeah—the connection to the Internet. It was really the only negative they pointed out, which obviously meant a lot to them.*"

This was confirmed by other respondents, including one who when asked why he thought a review was positive, responded:

> "*I think generally the comments were fairly positive. Obviously there were some comments in there where the author you know highlighted missing features or things they didn't quite like. But I think overwhelmingly the tone of the review was quite positive—it sounded like the reviewer liked the phone, but they just acknowledged some small issues with it.*"

Thus, it appears that this is a key approach utilized by participants to evaluate whether a review is positive or negative, based on their responses. All six respondents mentioned this factor.

5.1.3 Explicit statements

Explicit statements refer to whether the review stated directly that it was a positive or negative review of the product. Examples of these include star-ratings, as well as statements within reviews identified by participants, such as: "*And he even recommends the phone to other users. So that makes it a positive review*." This appears to have served as a direct cue as to what the reviewer's intention was, as perceived by the participant. An example of this given by one respondent was: "*The end statement—because they said that it was a bad phone and didn't recommend it—that was the only thing that really gave off a really negative view*." However, this was not a huge influence, with respondents identifying that this was secondary compared to the overall balance of positive/negative features, with one participant remarking: "*There's also that comment made on the line below that where it says 'Recommended: Yes'. But I didn't really pay much attention to that; I was more interested in the content that was written*." This idea of explicit statements was mentioned by all six participants.

5.1.4 Presence of very negative description of features

While a review may have discussed many positive features, participants identified that a sufficiently in-depth, strongly negative depiction of one or more features could shift their opinion towards believing it was a negative review. This is clearly shown in the following quote by one participant, in relation to whether the respondent would be more or less likely to purchase the product: "*…mostly because the feature he finds irritating, sounds to me like a genuine concern. And I think it might affect me too if I buy this phone*." However, there was no similar effect if an individual feature was discussed in a strongly positive manner, with participants not identifying this in their responses during the interviews. Thus, the current evidence suggests that it is a one-direction relationship: if the author heavily emphasized a negative aspect, a review may be perceived as negative despite the overall balance of positive/negative features discussed, or any explicit statements within the review. Four respondents mentioned this factor.

5.1.5 Semantic orientation of words

Semantic orientation of words was stated by a number of participants as how they knew whether a feature discussed was positive or negative. This is perhaps most clearly exhibited in a statement by a participant, where the strong, semantically orientated language is clearly noted: "*Yeah, I think so. I mean, it's the repetitiveness, it's not just that they've said 'I love this' and that's it. They've said love, love, love, love, love … I can count four or five just there*." It appears that the semantic orientation of a word, as stated by the review author, indicates to the reader whether they are talking about that in a positive or negative manner, and the degree to which the item discussed is positive or negative. In particular, this was observed most often when strong, emotive language was used, such as the prevalent use of "ugly" in one review to describe a feature perceived as negative, on which one participant remarked: "*But I think me personally—they've put me off by describing it as a brick, as ugly, as hideous*." Thus,

while this is an idea commonly identified by the respondents, it does not operate independently: rather, it appears to serve in support of other factors identified, based on the respondents' descriptions. Overall, four respondents identified this factor.

5.1.6 Factors not associated with positive/negative alignment

The following sub-headings outline factors which do not appear to exhibit a relationship with positive/negative orientation, as addressed by opinion mining, but instead appear to be related to other aspects or outcomes derived by reading a review.

5.1.7 Range of features covered

The range of features covered in a review was frequently mentioned throughout the interviews. Participants clearly stated that they wanted a broad range of features discussed in a review, with one participant stating:

> "*I would not purchase the phone because they've pointed out to me very quickly the things that are lacking, that they … they've written it in such a way that they've covered all the things that people would expect to be talked about.*"

This is an interesting factor identified through this research, in that it appears that participants associate the range of features covered with the author's credibility: indicating how long they have utilized the product. A participant stated it as: "*Yeah, it's basically like they've gone into a shop, picked up the phone, they've trailed it maybe even; and then wrote a quick description of why they liked it. Rather than they haven't gone into any intricate features.*"

5.1.8 Depth of description of features

The depth of description around each feature was also identified as important by research participants. It was commonly observed that readers want informative depth in reviews: particularly around how well the features perform, with one respondent stating that: "*I want to know how well the phone actually works, whether its features do what they say, and how well everything fits together.*" It appears that this factor exists in some relationship with the range of features covered, with respondents often mentioning they wanted both from a review:

> "*Like I said before, covers all the main functions of the phone, it's not too long, it's not too technical. It's written a quite easy to read way, and yeah, I think it's about the right length … Because I think people who do look online to read reviews are going to be looking at a lot of reviews. Either on the same phone or of a whole bunch of phones that they're trying to compare, and they don't want to be reading essays. And at the same time, they don't want little tidbits because they actually want enough information to make an informed decision.*"

This also encompasses participants' statements about how they needed explanations of what features do, rather than raw technical statements. One participant expressed this as: "*I mean, I'm not going to read the types of chips they use or*

whatever—I don't care. I'm more interested about functionality than what technology they're using." This factor thus incorporates some material which was initially coded to technical descriptions, based on the fact that this code represents a desire on the part of participants for a thorough, accessible explanation of what a feature does, and how it achieves benefits for the end-user.

5.1.9 Perceived objectivity of review

The objectivity of the review, as perceived by the participants, was also identified throughout the interviews. One respondent, when asked what aspect of a review he/she preferred—technical details or personal anecdotes—said:

> "*... The second aspect to it as well is do I trust the person's opinion. So this case it seemed like it's just a review posted on an online shop or something like that by some random person. The weighting I'd give to someone's opinion would vary a lot depending on who that person is. So that if it was a reviewer ... a bit more weighting than just some anonymous review that could have been posted by anyone—it could have been posted by anyone. It could by someone from Nokia, for all intents and purposes. So there's that aspect to it as well*."

It thus appears that participants are acutely aware of the role of the author in writing a review, and are conscious of how review text is used to persuade people about the product being reviewed. It appears that factual information (or the absence of it)—such as technical numbers—help make a review appear more objective; when asked if they thought a review was in-depth, one respondent replied: "*Still because it was very informal. It was quite a lot about its aesthetic values, rather—as I mentioned earlier—than its technical details. And I think, and yeah, I don't really care if they think it's ugly, or if the battery's huge*." However, it appears that the presence of explicit opinions, such as personal views about the potential users of a product, can have a significant impact on the overall perception of the review as a credible source of information, with one respondent stating: "*The phrase where 'blame the user not the product,' which made me think that it's a useless review*."

5.1.10 Formality of language

The formality of the language used in a review—whether the review is written in a disciplined, "professional" style, or with heavy use of emotive language and colloquialisms—is also significant in shaping review interpretation by the participants. Participants mentioned this issue regarding the formality of a review, and its impact upon them, as shown by the following statement: "*And I think that is more formal, it's more professional. They've obviously spent a bit of time playing around with the phone, and have thought about things more clearly*." It appears that respondents want user-contributed product reviews they read to be formal, although whether that is due to formal (in style) reviews being perceived as more authoritative, or due to another factor is unclear based on the transcripts analyzed.

5.1.11 Discussion of non-product aspects

Discussion of non-product aspects refers to instances where the review discussed things considered irrelevant by the participant reading the review. In the review corpus used, this was most commonly associated with discussion of a US-based service provider, whom the product would not be associated with in New Zealand. Respondents were often confused by the presence of these aspects, with one participant stating:

> "*Well this, I think, they, this reviewer is talking about the phone. It's fine if we are talking about Nokia customer care, but why are they use this Cingular services as an upgrading option is something else—I mean, they are service providers so*."

It appears that when respondents read a review, they are predominantly focused on what information they can obtain, with such "extraneous" information serving to distract from—rather than add to—the purpose of the review. However, one respondent did clarify this, stating that their concern about information in a review would depend on whether the feature would affect them or not, without expressing any discomfort with the presence of discussion of this aspect in the review:

> "*That would depend. If a device is tied to a Telco and I'm in that market, and I can only buy it from that Telco, then that would definitely have an impact. If this was a device—let's say a netbook or something like that—which you can typically buy independently of a Telco, then that'll be a different story altogether*."

Thus, extraneous information in one context may not be extraneous in another context; it is heavily shaped by the nature of the reader who is looking at the review.

5.1.12 Relevance of features to the reader

One factor, not contained directly within the reviews but very frequently mentioned, was respondents remarking on whether a review was "good" or "bad", based on how well it covered core features they used or envisioned using. One participant stated this as:

> "*Because if they're talking about the web browser here—and they're not very happy with the web browser in this review—however, I might not give a c— about web browser, that might be the last thing I'm concerned about. So I'll ignore that, and look at the other functions that I'm actually interested in*."

This suggests that users, while striving for an objective review (as identified above), are not seeking to analyze the reviews they read in a similarly objective manner: rather, the aspects discussed in a review are being interpreted based on how relevant they are to the reader. For example, a large amount of attention dedicated to one aspect of a product—while neglecting another aspect of the product—can result in readers expressing frustration at the reviews read, as exhibited in the following statement by one participant, when asked whether they felt the product was relevant for their needs:

"*Well I don't actually know, because they haven't talked about the messaging, and I text a lot. I know that it's got an easy menu, which means it's obviously easy to navigate to the messages, but I don't know anything about the messaging. Y'know, if it's got predictive text or if it's quick—if all the words come up on time as you're typing them, I don't know if it delays. All I know is that the calling is effective*."

It thus appears that a substantial amount of how much influence a review exerts is drawn from how well the aspects of the product discussed match with what the reader is interested in: an intuitive idea, if not previously addressed in the reviewed literature as affecting perception.

5.1.13 Comparisons to other products

Comparisons to other products refer to the degree to which the review compares the product reviewed with other similar products. This appears to exert an influence in several ways: by establishing whether the product is superior or worse (a direct statement) with a product the reader may be more familiar with; exhibiting depth or familiarity with products in the same area, supporting the positive ascertainment of how authoritative a reviewer is; and through providing a statement which leads readers to believe that this product is better or worse than a theoretical "baseline" of other products outside the review's focus. One of the respondents addressed this succinctly as:

"*I mean, first of all it depends on what the item is. Smaller value items I wouldn't pay as much attention; but in saying that I will often read the back of labels and stuff like that. But for items like mobile phones and so on I definitely will compare them other devices that I might be a bit more familiar with. So in this case the Nokia E62 I don't know much about, but I know a bit more about say one of their competitors' products, then I would compare the two, look at what the comments are across the two, and preferably try to find a review where the reviewer has used both devices, and see what their thoughts are.*"

5.2 Survey

A follow up survey was constructed based on the initial findings from the interviews and literature. Sixteen questions were developed focusing on textual factors of online reviews. The survey asked the participants to rate each statement on how it will influence their purchase decision based on a Likert scale ranging from 1 to 7 where 1 is "strongly disagree" and 7 is "strongly agree." A total of 136 surveys were collected. There were slightly more male (78) than female (58) participants. A majority of the participants were between 21 and 35 years old (97.8 %). These participants represent the targeted group of consumers. Moreover approximately half of the participants were students and the other half were working people. Table 3 depicts the demographic information of the participants. The results of the survey are shown in Table 4. Interesting aspects of the statistics will now be discussed.

Table 3 Descriptive statistics

Demographics	Frequency ($N = 136$)	
Age group		
16–20	1	0.7 %
21–25	88	64.7 %
26–30	30	22.1 %
31–35	15	11.0 %
36–40	2	1.5 %
Gender		
Female	58	42.6 %
Male	78	57.4 %
Occupation		
Company executive	36	26.5 %
Education	14	10.3 %
Housewife	2	1.5 %
Professional	16	11.8 %
Student	67	49.3 %
Others	1	0.7 %
How many online reviews do you read before making a purchase decision?		
<5		
>15	28	20.6 %
10–15	30	22.1 %
5–10	29	21.3 %
Never	38	27.9 %
	11	8.1 %

5.3 Highly influential factors

Based on the statistics presented above, it appears that the research participants felt that measures related to the likelihood of influence upon perception generally rate higher for metrics related to the information available in a review: Accuracy, Comparisons to other products, Information around customer support, Overall star-ratings, Technical information, and Persuasive words. This further suggests that individuals read reviews not only to gather information about a product but also information about product customer service to support decision making. In order to support their decision making consumers read a few online reviews to further ascertain the accuracy of the information. Other information—such as personal anecdotes and the formality of the review—may contribute some value, but could also be seen to some extent to be extraneous. This is in line with the consumer behavior model presented by Engel, Blackwell and Kollat [12], with the idea of "search" involving information about products, rather than any other information contained in product reviews. It does appear that each of the information availability metrics can be linked to the factors identified in the interviews.

Table 4 Overall ranking of responses

$N = 136$	Min	Max	Mean	SD
The accuracy of the information in an online review influences my purchase decision	3	7	5.74	0.951
The presence of product comparisons in an online review influences my purchase decision	2	7	5.62	0.959
The presence of information about the positive customer service/support of the product in an online review positively influences my purchase decision	3	7	5.60	0.801
The presence of an overall star-rating of the product in an online review influences my purchase decision	2	7	5.60	0.954
The presence of persuasive words in an online review influences my purchase decision	3	7	5.58	0.955
A review that contains detailed technical information influences my purchase decision	2	7	5.54	1.053
The presence of negative personal anecdotes of product use in an online review influences my purchase decision more than positive personal anecdotes of product use	2	7	5.49	1.054
Reviews that look formal and very professional positively influence my purchase decision more than casual reviews	1	7	5.43	1.203
An overall negative online review influences my purchase decision more strongly than an overall positive online review	2	7	5.38	1.155
Reviews that are more recent influence my purchase decision more than older reviews	2	7	5.29	1.123
A completely negative online review influences my purchase decision more strongly than a completely positive online review	2	7	5.28	1.292
The presence of other reviewers' ratings and comments in an online review influences my purchase decision	2	7	4.93	1.303
The presence of rude and racist words in an online review negatively influences my purchase decision	1	7	4.87	1.390
The presence of spelling and grammar mistakes in an online review negatively influences my purchase decision	2	7	4.63	1.321
An ambivalent/neutral review has no influence on my purchase decision	2	7	4.57	1.269
A very short online review negatively influences my purchase decision	2	7	4.46	1.305

$F(15, 2160) = 18.306$, $p < 0.001$

The presence of overall star-ratings—a form of explicit statement of positivity/negativity, as identified in the interviews—does appear to be particularly strong in the statistical measures of its relevance. This was identified by participants in their interviews around the use of explicit statements, and provides some corroborating evidence to suggest that these explicit statements contribute to substantial determinants of review influence. Furthermore, one aspect which this research was not designed to address, but which may still be of interest, is the manner in which individuals use star-ratings or similar to evaluate a product *without reading the review itself*. It could be that respondents are using these star-ratings to quickly browse through a number of products before they choose to read reviews on a smaller subset of products, discarding products which are consistently low on such ratings, while focusing their search efforts towards products which consistently rate high in such ratings.

The mean statistic describing the participants' responses towards the use of persuasive words is rather high. This could be related to the relatively high importance of marketing communication through persuasive influence. With participants seeing persuasive words and key words more as direct cues for establishing to what extent a product review was positive or negative, this could potentially exert influence on their decision making.

5.4 Less influential factors

From the statistics presented above, it appears that the research participants felt that measures related to the likelihood of influence upon perception generally rate lower for metrics not decisively related to the information decision making available in a review: the presence of rude and racist words, ambivalence/neutrality, spelling and grammar mistakes, brevity and other reviewers' ratings and comments. The statistics around completely negative reviews (reviews that are solely negative) and overall negative reviews (reviews that are generally negative, but not entirely) are interesting in that both scores were similar but were not at the high end of influence. This does suggest that readers may be somewhat skeptical of such completely positive/negative reviews, with a number of potential reasons for this skepticism. This could be due to fears expressed by some participants that some reviews are written in a style that suggests they were written by a marketer: one participant commented during their interview that part of their disdain for the use of online reviews when making a decision was that "*It may be a marketing person who's talking to me, and he influence me the way, and give me kinda some guarantee something*." It could thus be suggested that fears around the objectivity and purpose of the reviewer could be considered by participants as too positive or negative to be realistic depictions of the product. This could also have been amplified by the research design however: with the respondents asked to read more than one review on one product, completely positive or negative reviews would stand out compared to others which did mention deficiencies or positive aspects of the product.

Similar to completely positive/negative versus overall positive/negative, there appears to be a gap between both scales and that expressed for a review that was ambivalent (did not lean towards a positive or negative stance on the product). However, the argument of author legitimacy does not appear to be relevant in this case, with it appearing more likely that an ambivalent review suggests that the review simply did not contain enough information to allow the author (or the reader) to make a decision about the product. Given the heavy emphasis that was placed on features and information about features by participants, a review that does not provide sufficient information to allow decision making is less likely to meet readers' needs. Thus, such reviews are likely to be of less use to a reader, and to exert less influence on their decision making than more polemic reviews.

6 Discussion

Based on the results identified above, we analyze how well the results identified from the interviews and survey correspond to the conceptual model developed based

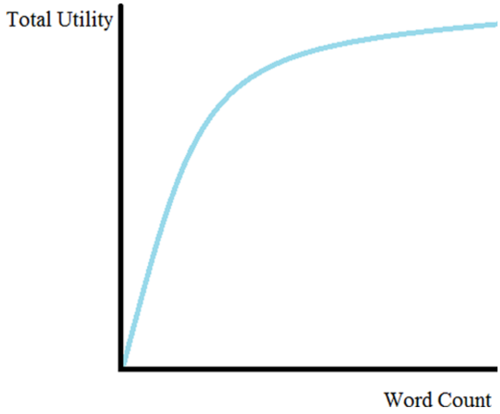

Fig. 4 Word count/utility graph

on the existing literature. An analysis of each factor in the established conceptual model—word length, overall positive/negative nature, keywords and quantitative information—will now be presented below.

6.1 Word length

Word length refers to the length of the review document, and appears to play a minor role in and of itself, rather serving as a suggestive metric for factors identified in the research results. There was no unidirectional relationship established between word length and perception, with participants remarking that word length could both be too short and too long: "*I only like a long review if I'm almost already decided whether I'm getting it or not, and I want to know in-depth detail.*" Rather, it appears that word length may be serving as an indicator of the information value contained in the review, with insufficiently long reviews lacking in information compared to the norm. However, this does not explain why longer reviews were also seen as undesirable. One way in which we can address this conundrum is by utilizing the economic concept of opportunity cost and marginal utility. The time spent reading an individual review is not free: it represents time that an individual could spend reading other reviews, or investigating other sources of information. Thus, an individual reading a review wishes to obtain as much value (information about the product) in a given amount of search time as possible. Reviews that are longer may offer less marginal utility for the increase in length: while the first sentence or two of a review may offer a significant amount of information, the longer it gets the more marginal the information contained is likely to be. Thus, we can diagram this relationship combined with the idea of marginal utility, as shown in Fig. 4.

This diagram could explain this anomaly. When the overall word count (representing length) of a review is low, the amount of total utility derived is insufficient (as represented on the y axis), but the increase in the curve between two points along the word count axis (represented on the x axis) is high. However, as this increase in word count continues, the amount of total utility gained for a proportional increase in word count diminishes, eventually flattening at some point. Thus, given an equal cost of reading an extra word, it is eventually no longer worthwhile to the reader to continue, based on the decreased utility they are gaining from reading that review.

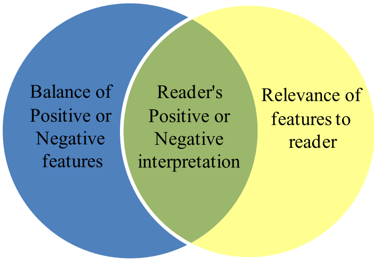

Fig. 5 Venn diagram of reader's positive/negative interpretation

It thus appears, as identified in the factors derived from the interviews and survey, that word count has a minor influence on the perception of a review, but only as a sub-component of the depth of feature information provided. This means that while it is relevant, it is not a stand-alone metric for ascertaining the positive/negative orientation of a review, or the influence exerted by a review on the decision making of the readers.

6.2 Overall positive/negative nature

The overall positive/negative nature of a review is generally approached by the Natural Language Processing academic sub-discipline as represented by semantic orientation. This factor is clearly exhibited in the research results. Indeed, it was so prevalent in interviews with the participants that it could be allocated its own section of the results (shown in results, above). This is clearly a significant aspect of how individuals interpret reviews: it is evident that the readers of product reviews are ascertaining whether it is positive or negative. However, while several statistical approaches have been proposed by NLP researchers, these heuristics appear to be too narrowly focused on analyzing the orientation of the words, while missing their context [7]. It appears that respondents are simply balancing the positive and negative aspects of a product discussed, moderating each comment by the semantic orientation of surrounding words, and using this approach to derive the *author's* overall perspective of the product. This does not, however, suggest whether the product is perceived as positive or negative *by the individual reading the review.* Rather, the way that the individual evaluates the review as positive or negative for their needs appears to be based on how well the features identified as positive or negative in the review match with the relevance of the features to the reader. This can be depicted in the Venn diagram (Fig. 5).

However, it also appears that the positive/negative nature of a review—while certainly affecting the perception of the review—is not enough alone to explain the overall perception. Indeed many of the factors identified from the interviews—such as objectivity—do not appear to be related to positivity/negativity, but instead address other elements of review perception not covered by the overall positive/negative nature of a review, such as the accuracy of the review as a source of information.

6.3 Keywords

Keywords—the use of lists of words or phrases, placed in context to extract meaning [19]—were also identified in the literature as one way in which the perception

of a review is shaped. This factor, while loosely defined for the purposes of this context (product reviews), initially appears to most closely correspond to what was identified as "features" in the interview responses. Given the significance of features as the information sought in the "search" phase of the consumer decision making processes [12], and the frequent mentions of product features within the interviews and in the survey, the interpretation of features as keywords appears the most fruitful in terms of establishing their relevance; although again, the definition provided in the literature is somewhat unclear around this. It can be concluded that the features identified as keywords are a significant part of individuals' perceptions of a review, although this is not the sole factor involved.

6.4 Quantitative information

The presence (or absence) of quantitative information—defined by Hsee et al. [23] as numbers that describe the underlying attributes of a product—also appears throughout the results of this research. Based on the direct questions asked around technical numbers in the interviews, respondents agreed that the numbers were useful, but were not enough by themselves without a context for their use established:

> "*Yes. Also technical information that would also not you know, give the technical information, but also explain why these particular, y'know, features are useful or not so useful, so people like myself who don't have a good knowledge of cellphone features and which are good or bad, so I know, 'oh, well they say this is a good point,' and so I understand what it is.*"

It thus appears that such quantitative information does strongly influence reader perception of a review, but only where this information relates to explaining or comparing features as depicted in the survey result, while quantitative information alone would have less influence on readers:

> "*Right, right. It's really about... this sort of review is really about whether they like something about it or dislike something about it. It's as simple as that. There's no care about numbers or technical information, and I think the person reading it—myself—when they read this sort of review acknowledges that that's case, and that I also don't care at this point.*"

It thus appears that quantitative information, as identified by the literature, is a subcomponent of providing depth in the explanation of features, rather than being a direct measure or determinant of reader perception of a review, with one respondent putting it as:

> "*Well I would say they could put technical information, but I don't really understand that much technical, but what I'm saying is the features that should be mentioned, not in the technical term—otherwise I will not understand—but the features should be mentioned.*"

7 Conclusions

Based on the research question identified at the commencement of this research—*What are the relevant factors in a product review and to what extent do they influence*

the readers' decision making regarding the product?—we conclude that these textual factors within a review have been successfully identified through qualitative and quantitative methods. From our survey, it appears that the research participants felt that measures related to the likelihood of influence upon perception generally rate higher for metrics related to the information available in a review—Accuracy, Comparisons to other products, Information around customer support, Overall star-rating, Technical information, and Persuasive words. On the other hand, the presence of rude and racist words, ambivalence/neutrality, spelling and grammar mistakes, brevity and other reviewers' ratings and comments are less influential. This research has been verified based on a conceptual model which resolves this question. The model does process strong levels of content validity of explanatory power, potentially facilitating an algorithmic approach for the automatic evaluation of influence.

This research presents a range of opportunities and implications both for academic research in this area, and for the development of systems by practitioners. However, it does exhibit certain limitations. Firstly, the samples were collected from a specific country, mainly China. As different countries would have different levels of e-commerce adoption and cultural influence may modify purchase behaviors, the findings from this study should be generalized with caution. Secondly, this study used mobile phones as an example. It is reasonable to expect that only products with features and values that are similar to the experiment artifact would produce similar results. Other fashionable products such clothing, shoes, perfumes, and accessories would need to be further validated. Lastly, this study focused on textual information within online reviews. Other external factors such as advertising and pop-ups, peer recommendations, web site reliability and credibility were not investigated. It is reasonable to expect that these factors would have some influence on consumers' purchase decisions while reading online reviews.

Hence future research will focus on expanding the influential factors in the consumer decision model to include more comprehensive factors such as the characteristics of the online review site, the reputation of the reviewers, the consumer values and the product values.

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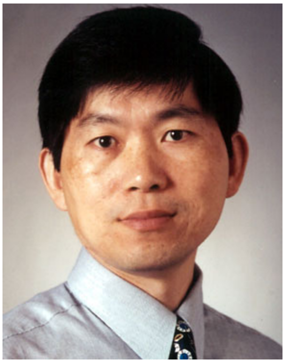

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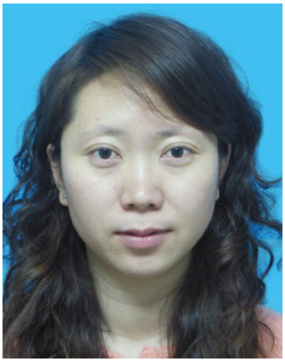

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